

## Extracting an Extremely Corrupted ECG Signal

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The electrocardiogram (ECG) signal is vulnerable to various noise interferences during recording, which compromises the precision of subsequent diagnosis. ECG readings, essential for detecting cardiovascular disorders, are highly susceptible to noise, notably power line interference (PLI) at frequencies of 50 or 60 Hz. Severe PLI can obscure or completely conceal specific components, such as P-waves and QRS complexes. The extraction of untainted ECG signals from polluted data is a fundamental difficulty in biomedical signal processing. This paper introduces an adaptive experimental technique for removing the 50Hz power line component from a severely damaged ECG signal by employing iterative 50Hz subtraction circuits and high-order low-pass filters to eliminate various harmonics of 50Hz and other noise sources. The experimental results completely correspond with the design methodology. The resulting ECG signal is suitable for cardiovascular diagnostics. The implemented circuit is low-cost, and all its components are readily available on the market. This device can extract a pristine ECG signal from a noisy environment.

**Keywords:** Adaptive filtering, ECG spectrum, ECG extraction methods, Electrocardiographic, Power line removal, QRS-complex.

Various forms of power line interference (PLI) at 50/60 Hz typically alter biomedical measures, including ECG signals, leading to erroneous disease diagnosis. A novel technique for eliminating power line interference (PLI) from electrocardiogram (ECG) readings was developed by employing an orthogonal basis to distinguish between signal and noise.<sup>1</sup> The technique was simple, computationally efficient, and superior to current methods at that time. It was simulated and assessed in MATLAB, resulting in enhanced signal quality.<sup>1</sup> Several methods were applied through the use of difference equations to determine the ideal initial weights for adaptive filters. The derived analytical response of such methods determines

the suitable weights and indicates that the mean squared error is contingent upon the initial weight.<sup>2</sup> The proposed method was utilized to eradicate the known frequency PLI signal in the ECG signal. The PLI signal was recognized as a composite of sinusoidal signals. The adaptive filter endeavors to modify the amplitudes of these sinusoidal signals to prepare a reference signal closely resembling the contaminated PLI signal. Noise cancellation in ECG signals is crucial for identifying features, with PLI being the main noise source. Digital notch filters effectively attenuate interference, but transient interferences and ringing effects occur. An adaptive notch filter (ANF) can be used to improve PLI cancellation.

An algorithm required a rapid Fourier transform, and used a spectrum correction was proposed to estimate harmonic parameters.<sup>3</sup> The compensating signal was integrated from multiple Fast Fourier Transform (FFT) spectrum bins, reducing PLI. The proposed ANF required no parameter specification, surpassing traditional notch filters. Signal analysis is a sophisticated procedure that automates data evaluation, especially within the medical domain. Physiological signals are progressively utilized, particularly in extensive datasets comprising thousands of characteristics.<sup>3</sup> A review was presented to examine ECG signals and feature extraction approaches pertinent to digital health and artificial intelligence (AI) applications.<sup>4</sup> Feature extraction diminishes signal dimensionality and facilitates data compaction, hence enhancing the efficiency of machine learning and deep learning models. The review addressed ECG signal processing and feature extraction across many domains, offered pseudocode for replication, examined deep features and machine learning integration, and contemplated future advancements in feature extraction for ECG signal analysis. PLI may distort biological records, resulting in erroneous disease diagnosis. Effective interference mitigation strategies are required to eradicate these interferences without jeopardizing intrinsic signal characteristics. A revised methodology utilizing the variational mode decomposition technique was introduced to eradicate PLI from ECG signals.<sup>5</sup> The method established the core frequency of an intrinsic mode function to correspond with the normalized power line disturbance frequency. The experimental results indicated that the PLI signal was precisely captured in both magnitude and phase and then removed. The proposed methodology was evaluated using ECG signal recordings from the MIT-BIH (Massachusetts Institute of Technology–Beth Israel Hospital) Arrhythmia database and compared against traditional notch filtering techniques. An effective ECG denoising method utilizing empirical mode decomposition (EMD), sample entropy, and an enhanced threshold function was proposed to eliminate noise from ECG data, hence enhancing diagnostic accuracy for automated medical systems.<sup>6</sup> The procedure had three phases: EMD decomposition, novel threshold function denoising, and signal reconstruction and smoothing. Simulation results demonstrate

that the approach is resilient to several noise types and enhances both signal to noise ratio (SNR) and mean square error (MSE). The noise removal technique suggested in for ECG signals is an efficacious strategy to enhance diagnostic capabilities in automated medical systems.<sup>7</sup> It tackles the problem of noise in ECG signals, which can be alleviated by an adaptive mechanism. The technology is consistent with current ECG noise reduction techniques and can substantially improve heart state assessment. A methodology for PLI removal in ECG data, devoid of thresholding methods, entailed detecting the frequency ranges of the ECG and noise, nullifying wavelet detail coefficients, and augmenting the signal by the inverse discrete wavelet transform.<sup>8</sup> The optimal wavelet function for denoising was Symlet 8, which outperformed thresholding and notch filter approaches for 75% of synthetic signals and 100% of real signals. The method was applicable for high-frequency denoising without prior knowledge of the frequency.<sup>8</sup> ECG interference in intensive care unit (ICU) patients can compromise diaphragm electromyogram (EMGdi) signals.<sup>9</sup> Estimated ECG Subtraction (EES) is a method that removes ECG interference from esophageal EMGdi recordings. It involves determining ECG artifact timing, estimating normalized ECG, and subtracting denormalized ECG estimates.<sup>9</sup> This method surpasses wavelet-based filters and improves therapeutic diaphragm activity monitoring. A comparison of various methods for correcting baseline drift in ECG signals was presented.<sup>10</sup> A novel adaptive technique for the rectification of baseline drift was proposed. The approach involved modifying the reference signal of the adaptive filter by multiresolution wavelet transformations of the ECG signal. Various baseline drift correction approaches were evaluated for their efficacy in processing model ECG signals affected by baseline drift of differing strengths. The method for subtracting PLI from high sample rate ECG signals was discussed and implemented with modifications to guarantee efficient removal.<sup>11</sup> It suggested a methodology to address frequency deviation; and introduced a revised procedure implementation program. Results from the simulated tests were also disclosed. ECG signals often contain residual PLI, and various methods have been developed to reduce interference. The

subtraction process is known for eliminating interference while preserving the signal spectrum. The PLI is derived from the distorted signal using a second-order band-pass filter, with minimal phase error. The subtraction process is used to rectify discrepancies between moving averaged PLI signal samples and their actual positions.<sup>12</sup> A PLI reduction method utilizing a current-reused current-feedback instrumentation amplifier (CFIA) for ECG recording was established to inhibit the unwanted PLI from compromising the quality of ECG recordings by constraining an input common-mode voltage to the saturation region of the input transistor of the CFIA.<sup>13</sup> The proposed circuit exhibited a total power consumption of 18 W at 1.8 V.

The frequency spectrum of the ECG signal is very important in its detection and ~~diagnose~~ diagnostic purposes. A new method for identifying ventricular fibrillation (VF) in brief ECG episodes was developed.<sup>14</sup> VF is a common arrhythmia in cardiac arrest patients, and its detection is crucial for timely defibrillation. The method used stochastic waveforms and a deterministic Probability Density Function for physical variations. It outperformed nine established VF detection algorithms, providing new insights into VF dynamics. The efficacy of wavelet transform-based QRS detection was evaluated against the Pan Tompkins method and derivative-based QRS detection, emphasizing sensitivity, accuracy, positive predictive value, and detection error.<sup>15</sup> The proposed methodology attained an accuracy of 93.35% and a specificity of 90%, surpassing current methods in the detection of QRS complexes in ECG signals. A study introduced an effective system for evaluating the quality of mobile electrocardiogram (ECG) signals.<sup>16</sup> The method employed heuristic fusion and fuzzy assessment of Signal Quality Indexes (SQIs) across many parameters. The methodology comprised two components: quantification and extraction of SQIs, and intelligent evaluation and classification. The approach attained an accuracy of 97.67%, sensitivity of 96.33%, and specificity of 98.33% on the training set, and 94.67%, 90.33%, and 93.00% on the test datasets. Numerical approaches to interpret ECG signals and detect the QRS complex, utilizing data from cardiac monitoring, were addressed.<sup>17</sup> The study evaluated wavelet transforms' fundamental functionalities on

1000 data points, providing valuable insights into individual health. Convolutional neural networks (CNNs) were employed to assess and utilize pre-trained higher-order spectral estimations of cardiac arrhythmias in electrocardiograms (ECGs).<sup>18</sup> The research utilized transfer learning techniques with pre-trained convolutional neural networks, specifically AlexNet and GoogleNet, for the automated diagnosis of ECG arrhythmias. The system attained an average accuracy of 97.8% utilizing third cumulants and GoogleNet, establishing it as an efficient automatic cardiac arrhythmia categorization technique. ECG is a prevalent method for documenting the electrical activity of the human heart. Precise computer analysis of ECG signals is difficult due to their susceptibility to high-frequency noise and numerous distortions resulting from their low amplitude. In remote healthcare systems, the sophisticated analysis of ECG signals is conducted by powerful machine learning algorithms. The precision of these methods depends on the Signal-to-Noise Ratio (SNR) of the input ECG signal.<sup>19</sup> Cardiovascular illnesses pose a significant risk to life, and the analysis of ECG signals is essential for diagnosis and arrhythmia identification. A feature extraction technique utilizing bispectrum and 2D graph Fourier transform was devised to derive features from eigenvalues, employing a Radial Basis Function Support Vector Machine (SVM-RBF) for the classification of arrhythmic heartbeats.<sup>20</sup> The model attained a classification accuracy of 96.2%, as per cross-validation findings. Ventricular arrhythmias (VA) are abnormal, rapid heart rhythms caused by erroneous electrical impulses in the heart's ventricles. A novel deep learning methodology employs nonlinear ECG signals for the detection of ventricular arrhythmias (VA). The procedure entails converting ECG signals into novel images, normalizing these images, training models, extracting deep features, fusing features, selecting the optimal features, and employing supervised learning classifiers.<sup>21</sup> The MIT-BIH dataset attained an accuracy of 97.6%.<sup>21</sup> In a 12-lead electrocardiogram (ECG) assessment, the ECG signals frequently exhibit low-quality data issues attributable to high-frequency noise from muscular activity and low-frequency noise from bodily movement and respiration. These issues result in delays in examination outcomes and

escalate medical expenses. Addressing issues related to low-quality and absent ECG data can enhance patient care, hence decreasing productivity loss and healthcare expenses.<sup>22</sup> This study aims to create a signal restoration model for each of the 12 signals to address the issues of low-quality and missing data resulting from mechanical and operator faults during 12-lead ECG tests. ECG signals are invariably compromised by numerous types of noise during acquisition and transmission. The presence of noise may generate inaccurate information on cardiac health, thereby hindering specialists from conducting accurate analyses. ECG signals are consistently affected by several forms of noise during acquisition and transmission. Noise may produce erroneous data regarding cardiac health, consequently obstructing doctors from doing precise assessments. A proficient methodology for denoising ECG signals utilizing a time-frequency framework grounded in S-transform and bi-dimensional empirical mode decomposition was introduced.<sup>23</sup> This approach maps an ECG signal into a subspace, decomposes the ST-based time-frequency representation, and subsequently employs non-local mean (NLM) to eliminate noise and restore the characteristics of the ECG signal. The method surpasses current wavelet-based techniques and NLM filtering, effectively attenuating noise while maintaining ECG signal attributes. A study examined the quality of an elderly individual's ECG signal using optical wireless links.<sup>24</sup> The system used infrared signals from an emitter on the wrist to detectors on the ceiling. The study used signal quality indexes (SQIs) to assess the signal's spectral and statistical features. The methodology simulated the entire ECG process, considering the elderly's mobility. Results showed optical wireless communication technologies can reliably monitor ECGs, with superior quality achieved with a minimum signal-to-noise ratio. The CardioGPT model is employed to analyze electrocardiograms through natural language, representing an innovative method for ECG classification.<sup>25</sup> The model was utilized on a dataset of ECGs from adult patients, featuring 60 unique rhythms or conduction anomalies described by cardiologists. The model was assessed utilizing Bilingual Evaluation Understudy (BLEU) and Recall-Oriented Understudy for Gisting Evaluation (ROUGE) metrics. The results demonstrated

favorable performance metrics across many evaluation criteria, with the CardioGPT model attaining elevated scores in BLEU and ROUGE. The model tackles the issue of imbalanced learning in ECG classification tasks, offering significant insights into fundamental patterns and anomalies.

In this work, two sequential 4th order 72Hz lowpass filters, two subsequent subtraction circuitries, and a notch filter are mostly used to clean a damaged ECG signal from PLI components and other noises.

## MATERIALS AND METHODS

ECG signals indicate the heart's electric activity, causing contraction of heart muscle cells and depolarization of nearby cardiac cells.<sup>26</sup> The rapid flow of sodium ions causes the depolarization wave, while the cells recover and exhibit resting negative potential in a repolarization phase. The electric current surrounding the heart is caused by ion movement in cardiac muscle cells, and the ECG signal's structure and cyclic repetitive components like the P-QRS-T complex shown in Figure 1 provide crucial information about the heart's electrical conduction system.<sup>26</sup>

ECG signals are a crucial biomedical tool, but they pose challenges in registration, processing, and analysis due to their nonstationarity, noise susceptibility, and variability among individuals. The main sources of noise are the changes in body-electrode impedance, patient movement, and baseline wandering. Muscle disturbances, caused by patient movement or environmental temperature are challenging to manage due to their broad frequency spectrum. Power interferences, caused by high power devices, and impulse-type interferences, such as diathermy, are also significant disturbances. These disturbances affect ECG signals in various categories.<sup>8-10</sup> Here, ~~is introduced an experimental system~~ an experimental system is introduced for recovering severely vanished ECG signals due to power line interference. The adopted method focuses on removing the power line voltage component that obscures the targeted ECG signal. Since the waveform of the power line voltage is exposed to multiple harmonic distortions, it is recommended to treat this distortion within its component that masks the ECG signal required to be extracted for diagnosing cardiovascular

conditions. In the presented method, two wet electrodes are used to detect the ECG signal. Figure 2 shows the schematic design of the presented method.

The potential difference between the left and right hand electrodes is amplified using a differential amplifier. It is anticipated that the output of this amplifier will contain a very weak ECG signal that is masked by a PLI voltage component operating at 50 Hz. This component is likely exposed to multiple harmonic's-harmonic' distortions, including 100Hz, 150Hz, and other higher harmonics. A higher-order lowpass filter (LPF) with a cutoff frequency below 100 Hz can be used to reduce the distortion caused by numerous harmonics. The cutoff frequency  $f_H$  of the higher order LPF is set at 72 Hz in order to balance between maintaining the ECG signal and removing multiple harmonic's-harmonics' distortion. To reduce the complexity of the experimental circuit, an eighth-order LPF is utilized to approximately purify the 50Hz voltage component that obscures the weak ECG signal. To accomplish a greater reduction in the circuit complexity, the 8<sup>th</sup> order LPF is implemented using two successive 4<sup>th</sup> order LPFs. Each 4<sup>th</sup> order LPF is designed using four successive first order RC LPFs as shown in Figure 3. These first order LPFs are designed such that each filter circuit has negligible loading effect on preceding and next filter stages, thus the cutoff frequency  $f_H$  of the 1st order LPF can be given by<sup>27</sup>

$$f_H = \frac{1}{2\pi RC} \quad \dots(1)$$

Where  $R$  and  $C$  are the basic resistance and capacitance of the LPF components, respectively. The overall transfer function  $V_o/V_i$  of the 4<sup>th</sup> order LPF can be approximated at any frequency  $f$  to

$$\frac{V_o}{V_i} \cong \frac{1}{\left(1 + \frac{f}{f_H}\right)^4} \quad \dots(2)$$

For a cutoff frequency  $f_H$  of 72Hz and a filter resistance  $R$  of 0.22kΩ, the filter capacitance  $C$  is equated to 10μF. The 8<sup>th</sup> order LPF is implemented using two successive 4<sup>th</sup> LPFs separated by an operational amplifier (Op Amp) buffer as shown in Figure 4.

Figure 5 shows the frequency responses of 4<sup>th</sup> and 8<sup>th</sup> orders LPFs. The 8<sup>th</sup> order LPF reveals significant elimination of frequencies above 100Hz. The main task in this work is to recover the ECG signal obscured by PLI. This can be carried out by subtracting the power line component from the raw signal containing the weak ECG.

Since the raw ECG signal after the 8<sup>th</sup> order LPF contains almost a purified 50Hz component, it is possible to subtract this component by using a multiple feedback bandpass filter (MFBPF) and

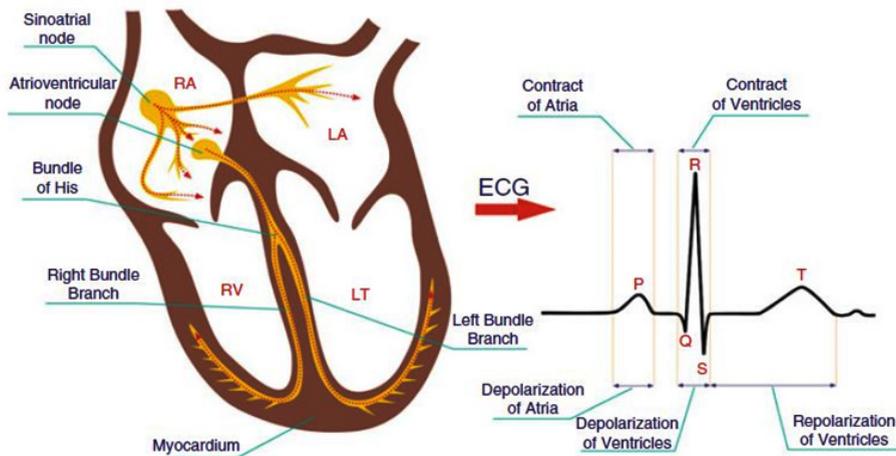


Fig. 1. The electrical activity of the heart. The T-wave represents ventricular repolarization<sup>26</sup>

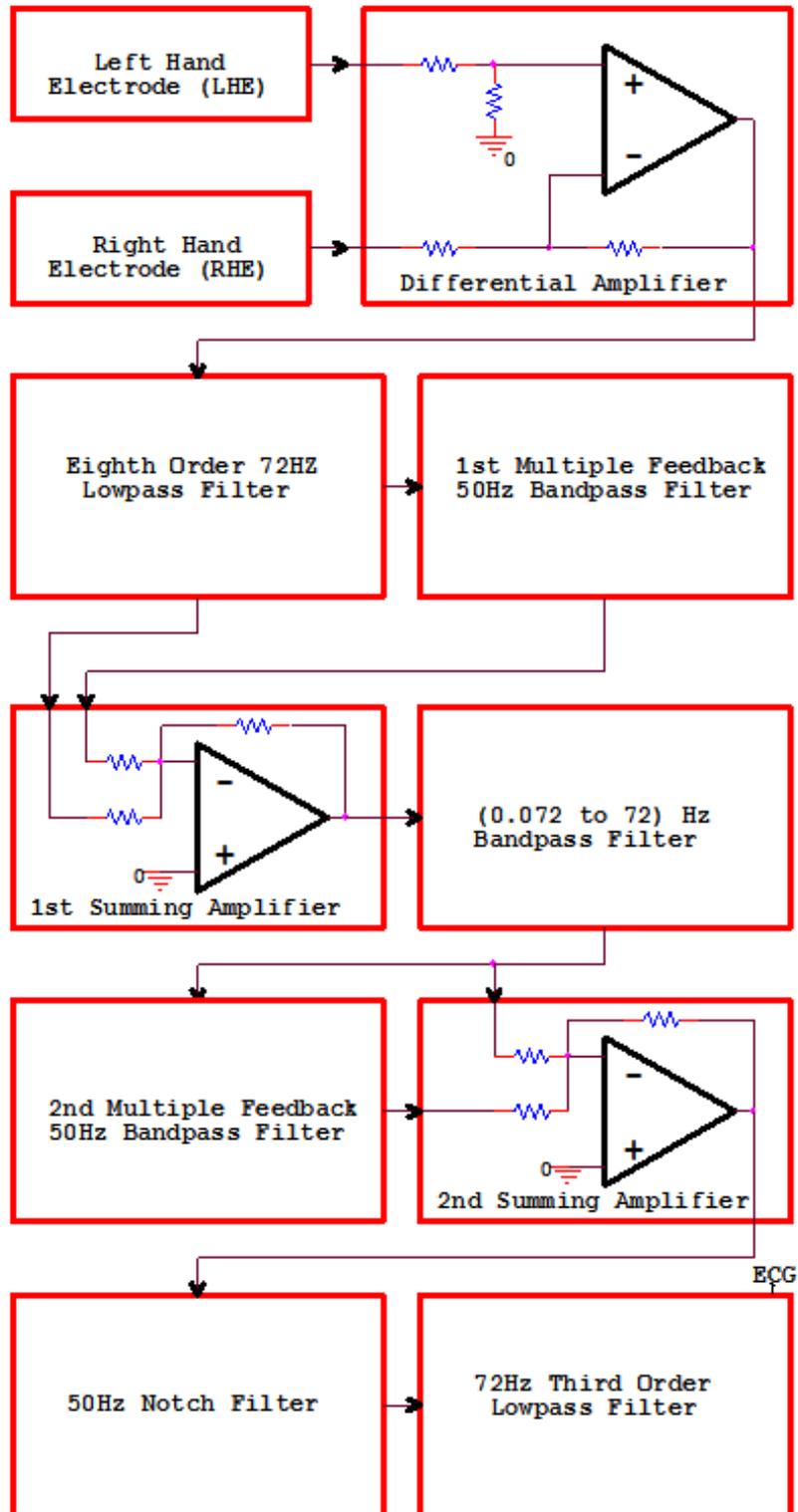


Fig. 2. Schematic design of the proposed method

a summing amplifier, as shown in Figure 6.

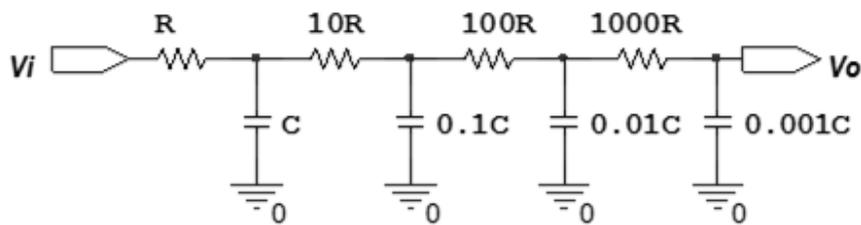
The MFBPF is designed such that it has a resonant frequency  $f_r$  of 50Hz and  $C_{1MF}=C_{2MF}=C_{MF}=100\text{nF}$ . The following design equations are applicable to this filter<sup>27</sup>

$$R_{2MF} = \frac{Q}{\pi f_r C_{MF}} \quad \dots(3)$$

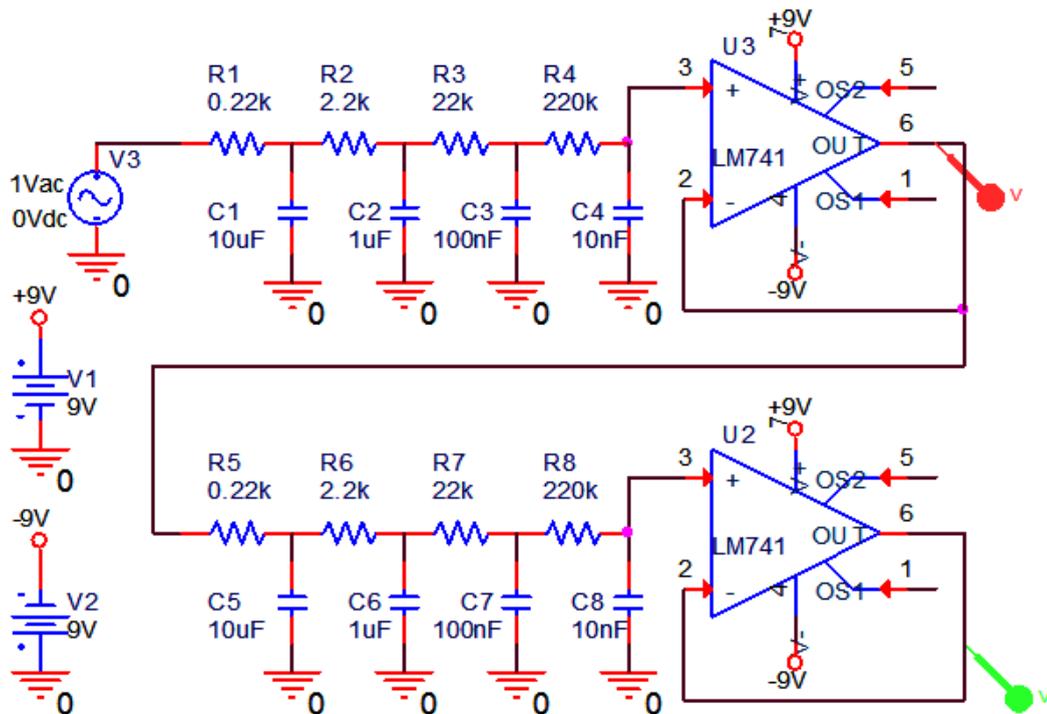
$$R_{1MF} = \frac{R_{2MF}}{4Q^2} \quad \dots(4)$$

$$A_{MAX} = \frac{R_{2MF}}{2R_{1MF}} \quad \dots(5)$$

Where,  $Q$  is the quality factor and  $A_{max}$  is the maximum gain at the resonance frequency. If



**Fig. 3.** Design procedure of the 4<sup>th</sup> order LPF.  $R$  and  $C$  are the basic resistance and capacitance of the LPF components, respectively



**Fig. 4.** Circuit design of the 8<sup>th</sup> order LPF

$f_R=50\text{Hz}$ ,  $C_{MF}=100\text{nF}$ , and  $A_{max}=5$ , then according to (3)–(5),  $Q$ ,  $R_{1MF}$ , and  $R_{2MF}$  will be 1.581, 10k $\Omega$ , and 100k $\Omega$ , respectively. The gain  $A_{max}$  is reversed at the resonant frequency  $f_R$ . The Op Amp LM741 is used to drive the MFBPF and summing inverting amplifier. Two 9V DC sources or batteries are used to operate the Op Amp. The summing amplifier is

designed such that it subtracts the output voltage of MFBPF from the main AC input. Note that the output of the summing amplifier reverses the AC input voltage components.

The frequency responses of MFBPF and the summing inverting amplifier are shown in Fig. 7. Since the output of the MFBPF exhibits a

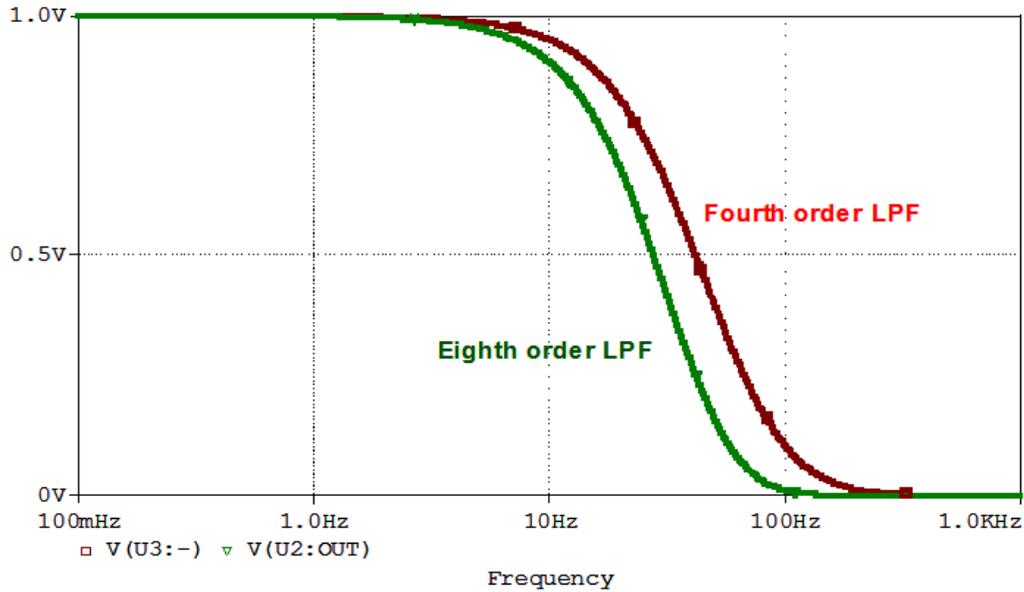


Fig. 5. Frequency responses of 4<sup>th</sup> and 8<sup>th</sup> orders LPFs

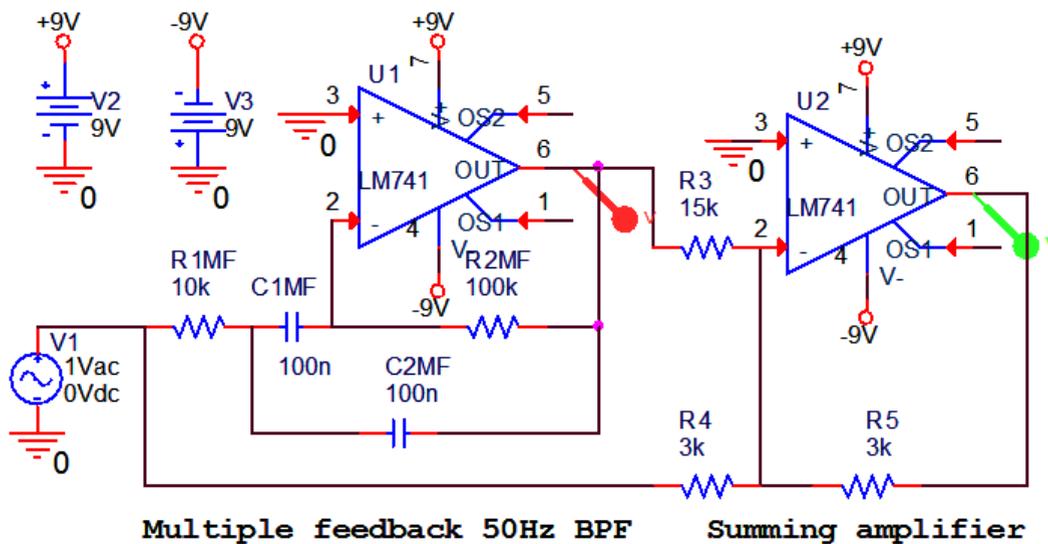


Fig. 6. The 50Hz subtraction circuitry

voltage level of 5V for an AC input amplitude of 1V, the gain values of the summing amplifier to the MFBBP output should be -0.2 or (-1/5) and -1 to the main AC input. Such gain values of the summing amplifier guarantee significant removal of the 50Hz voltage component from the input signal, as reflected by the response of the summing amplifier.

**Circuit design of the proposed extraction method**

Figure 8 shows a complete PSpice design of the proposed extraction method. A (0.72 to 72) Hz bandpass filter (BPF), which attenuates the frequencies above 72 Hz and prohibits very low frequencies, receives the output of the first summing amplifier as shown in Figure-Figures 2 and Figure-8. Furthermore, the DC offset linked to the processed raw signal is eliminated by this BPF. The output of this filter is anticipated to be a sinusoidal signal profile running at 50Hz and exhibiting an inverted ECG signal due to the inversion action of the first summing amplifier. The 50Hz notch filter is designed such that its cutoff frequency  $f_N$  is determined by<sup>27</sup>

$$f_N = \frac{1}{4\pi R_N C_N} \dots(6)$$

Where  $R_N$  and  $C_N$  are the basic design components of the notch filter. For  $C_N$  of 1 $\mu$ F,  $R_N$  is 1.591k $\Omega$ . In Figure 8,  $R_{27}=R_{28}=2R_N$ H+3.3k $\Omega$ ,

$C_{19}=C_{20}=C_N=1\mu$ F,  $R_{32}=R_N$ H+1.5k $\Omega$ , and  $C_{15}=2C_N$ H+2.2 $\mu$ F.

**The Experimental Prototype of the Proposed ECG Extraction Method**

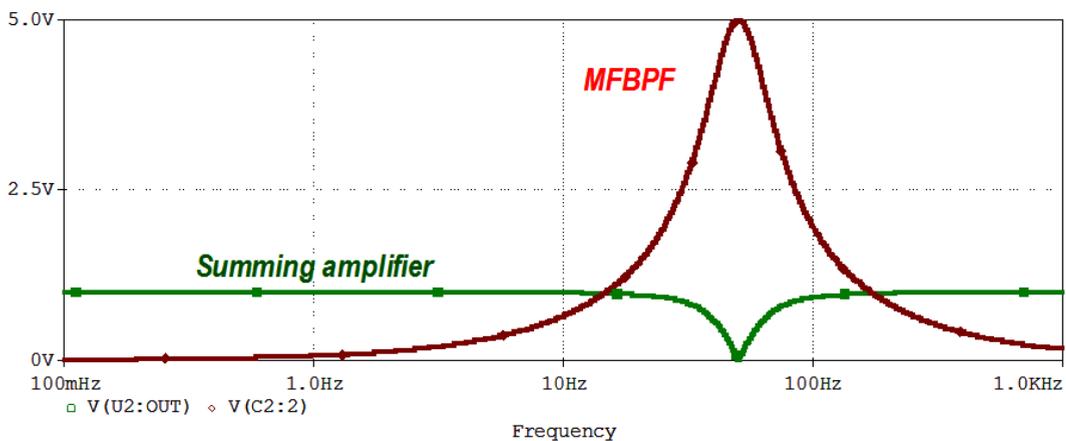
The circuit shown in Figure 8 is implemented using low-cost electronic components as shown in Figure 9. These components are commercially available. A digital oscilloscope is used to pick the experimental results. All electronic components are gathered on a single breadboard.

**RESULTS**

Two wet ECG electrodes are employed to capture the ECG signal from the human body. One electrode is affixed to the left arm, while the second is positioned on a matching location on the right arm. A 100Hz digital oscilloscope is employed to gather the experimental data. Figures 10-17 show the output signals at several locations inside the experimental circuit. Figure 10 illustrates the unprocessed ECG signal at the output of the differential amplifier. It exhibits an absence of an ECG signal.

Figure 11 shows the output of the second fourth-order 72Hz low-pass filter. It discloses an enhanced clean 50Hz sinusoidal waveform. This waveform is anticipated to include a vanishing or an-unseen ECG signal on its envelope.

Figure 12 illustrates the output of the first multiple feedback 50Hz bandpass filter. It demonstrates a pure power line voltage of 50Hz



**Fig. 7.** Typical Frequency responses of MFBBP and summing amplifier in the subtraction circuitry

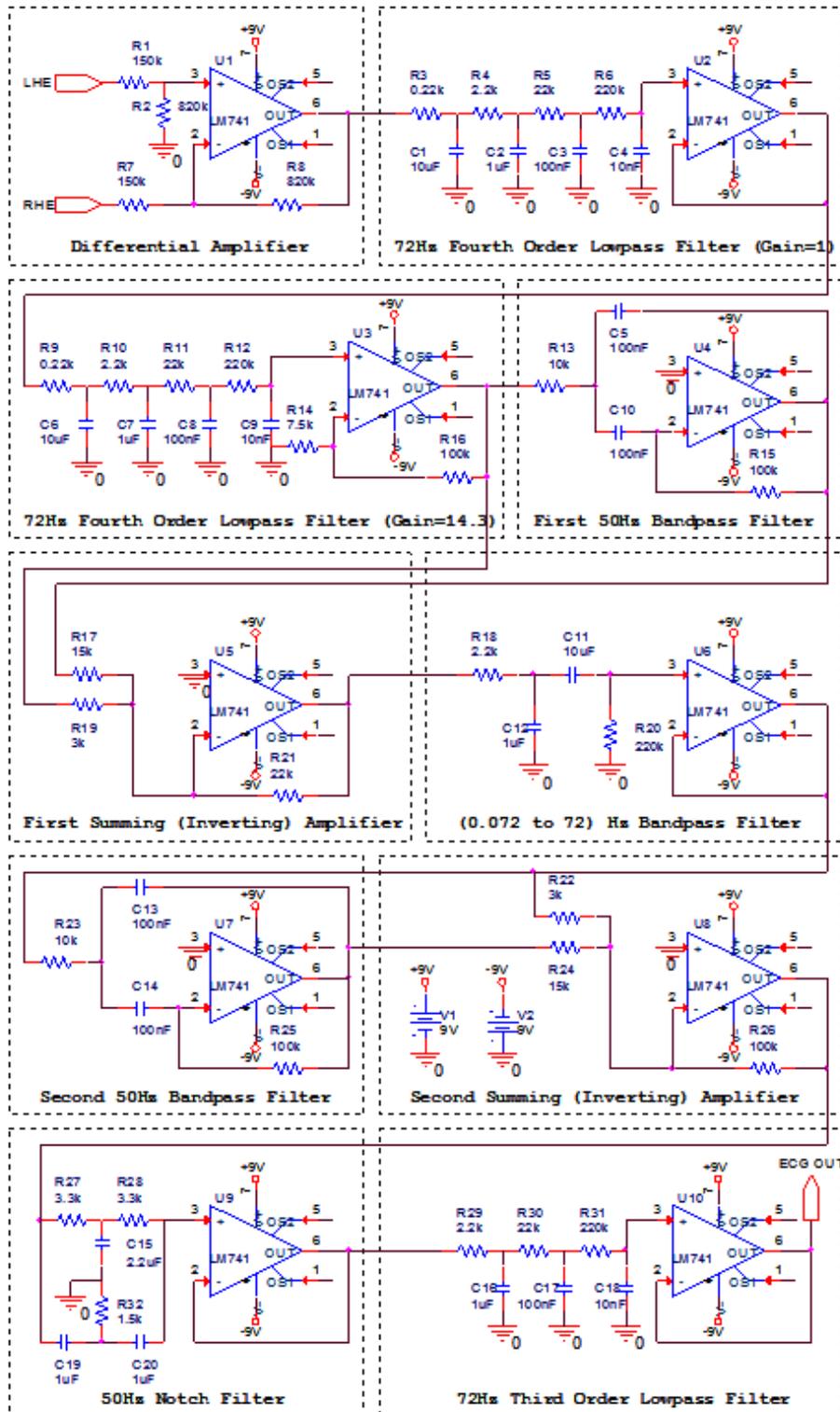


Fig. 8. Circuit design of the proposed method

with an amplitude five times that of its preceding stage (the second fourth-order low-pass filter). This waveform is anticipated to be mostly free from ECG contents.

Figure 13 illustrates the output of the initial summing inverting amplifier. The envelope of the acquired waveforms displays a discernible inverted representation of the ECG signal. This is due to the inverting action of the summing amplifier.

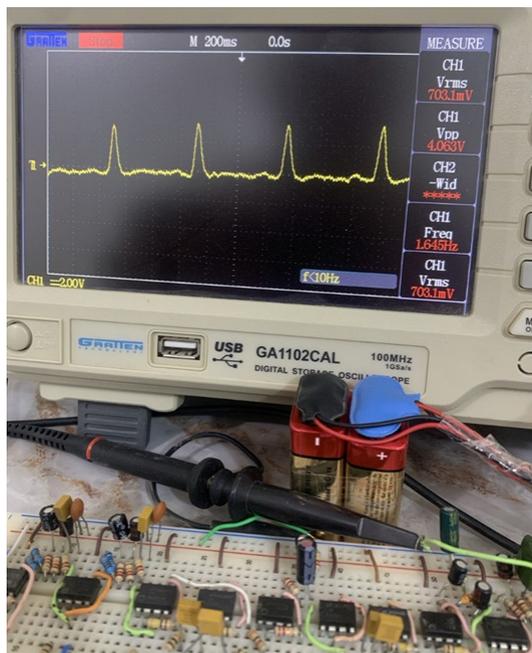


Fig. 9. A photo of the experimental circuit

Figure 14 displays the output of the second multiple feedback 50Hz bandpass filter. It indicates a fundamental power line frequency of 50Hz with an amplitude five times greater than that of its preceding stage (the (0.072-72) Hz bandpass filter). The anticipated function of the second multiple feedback 50Hz bandpass filter is a thorough cancellation of the frequency contents above 50Hz.

Figure 15 shows the output of the second summing amplifier. This figure demonstrates a substantial decrease in PLI and increased recognition in the extracted ECG signal.

Figure 16 shows the output of the notch filter. However, a noise component is present, which will be addressed in the final step of this design, represented by the third-order 50Hz low-pass filter.

Figure 17 shows the output of the final stage in this design, represented by the third-order 50Hz low-pass filter.

## DISCUSSION

The recovered ECG signal is obtained from a highly noisy environment. The majority of noise originates from voltage components caused by power line interference. The extracted ECG signal appears relatively clear, with all components distinctly visible, including the P-wave, QRS complex, and T-wave. The final ECG signal; experimentally obtained in this in this work exhibits a good form in comparison to those works mentioned in previous literature,<sup>6-10, 22-25</sup> most

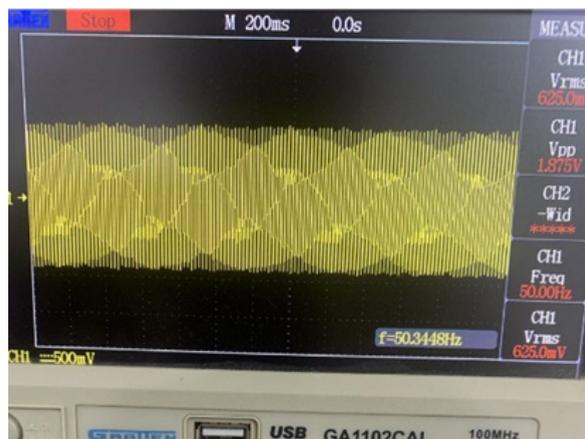


Fig. 10. The raw signal at the output of the differential amplifier (TB=200m/div)

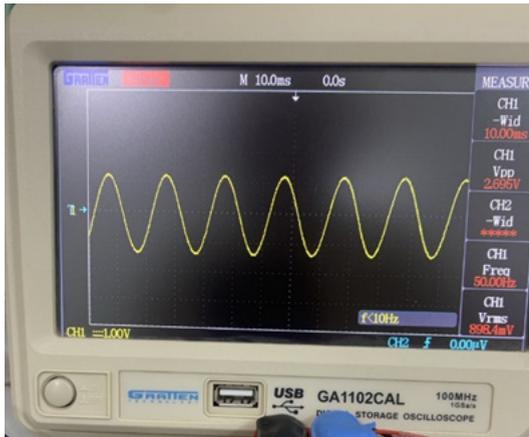


Fig. 11. The output of the second 4<sup>th</sup> order 72Hz LPF

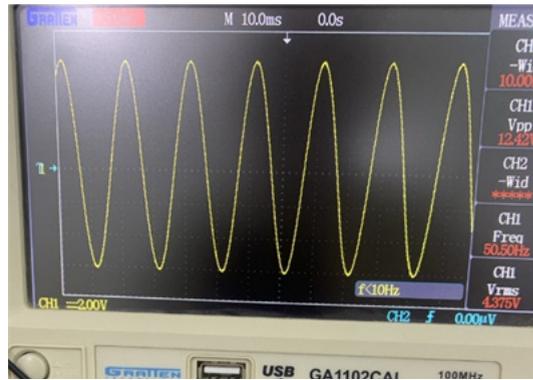


Fig. 12. The output of the first 50Hz MFBPF



Fig. 13. The output of the first summing amplifier

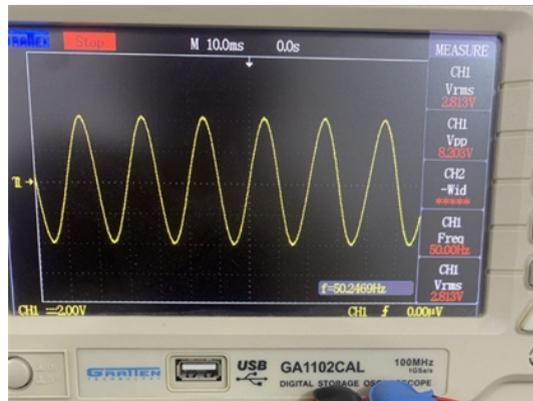


Fig. 14. The output of the second 50Hz MFBPF

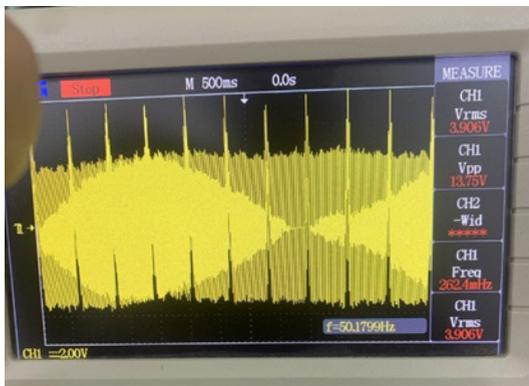


Fig. 15. The output of the second summing amplifier



Fig. 16. The output of the notch filter



**Fig. 17.** The final extracted ECG signal

of which were retrieved using various denoising techniques. The experimental results align with the expected output of each stage in the implemented prototype.

## CONCLUSION

The extraction of ECG signals, which use the heart's characteristic P, QRS, and T waveforms to capture electrical activity, is a crucial part of cardiac health monitoring. In order to recover a clean ECG signal from a completely corrupted raw signal caused by significant distortion from 50Hz power line interference and other potential sources of noise, a low-cost experimental circuit is proposed in this study. The main extraction strategy focuses on the removal of the 50Hz power line component from the raw ECG signal by using an adaptive filtering process and subtraction method. The sharp response of the MFBPF preserves the components of the ECG signal in the vicinity of 50Hz, which leads to better detection. The experimental results show a coincidence with the anticipated output of each stage in this design. The final extracted ECG is clean and suitable for the diagnosis of cardiovascular disorders.

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## Conflict of interest

There is no conflict of interest in this work.

## Data Availability

This statement does not apply to this article.

## Ethics Statement

This research did not involve human participants, animal subjects, or any material that requires ethical approval.

## Informed Consent Statement

This study did not involve human participants, and therefore, informed consent was not required.

## Clinical Trial Registration

This research does not involve any clinical trials.

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Not Applicable.

## Author Contributions

The sole author was responsible for the conceptualization, methodology, data collection, analysis, writing, and final approval of the manuscript.

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